May AI revolution be labour-friendly? Some micro evidence from the supply side

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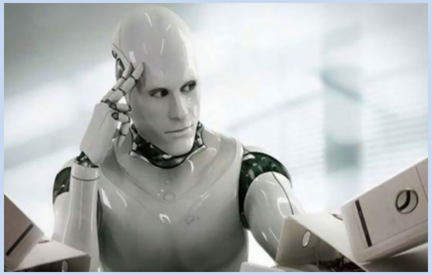
AIMS AND SCOPE

- Mainstream economists (particularly Acemoglu and Restrepo) put forward on the one hand an overall long-run and general equilibrium optimism (see below) and on the other hand a narrow empirical focus on the labour-saving impact of the solely robots on the user sectors, mainly car factories accounting for 40% of robot usage (see below).

- While most of the (recent) extant literature focuses on the demand side (that is the adoption of AI and robots as labour-saving process innovations in the downstream industries), there is a gap in the literature with regard to the supply side, that is the possible job-creation effect of AI technologies, conceived as product innovations in the upstream sectors.

- Within this framework, our study aims to assess the micro-level employment impact of AI and robotics, focusing on a worldwide set of 3,500 front-runner companies that patented the relevant technologies in the 2000 to 2016 time span.

TODAY ALARM…



- The past two decades have witnessed major developments in artificial intelligence (AI) technologies. As previous technological revolutions (think for instance to the diffusion of the ICT in the last decades of the past century), AI has a remarkable disrupting potential across firms, industries, economies and societies.
- The arrival of internet of things, self-driving autonomous cars (Tesla, Apple, Google) and widespread robots has raised again a fear of a new wave of '**technological unemployment**'.
- According to Brynjolfsson and McAfee (2011 and 2014), the root of the current employment problems is not the Great Recession, but rather a "Great Restructuring" characterized by an exponential growth in computers' processing speed having an ever-bigger impact on jobs, skills, and the whole economy: "**This time is different**".
- Moreover, not only agricultural and manufacturing employment appears at risk, but employees in services (Uber, airbnb, Amazon) - including **cognitive skills** - are no longer safe. Frey and Osborne (2017) predict that 47% of the occupational categories are at high risk of being automated, including a wide range of service/white-collar/cognitive tasks such as accountancy, logistics, legal works, translation and technical writing, etc.

CONVENTIONAL WISDOM (1)

- The “**substitution effect**”: tasks can be automated or not, depending on relative factor prices and the elasticity of substitution between capital and labor:
- *“ …When the wage rate is above the opportunity cost of labor (due to labor market frictions), firms will choose automation to save on labor costs,... ”* (Acemoglu and Restrepo, 2018a, *AER*, p. 1492).

- Both the conventional “**induced bias**” theory of innovation and the classical compensation mechanism “ **via decrease in wages**” are proposed again:

  ”These economic incentives [a change in the relative factor prices, ed.] *then imply that by reducing the effective cost of labor in the least complex tasks, automation discourages further automation and generates self-correcting force towards stability”*(*ibidem*, p. 1526; see also Acemoglu and Restrepo, 2019, *JEP*, p. 9).

- A second main self-correcting force is the “***productivity effect*** ”:

  “…,capital performs certain tasks more cheaply than labor used to. This reduces the prices of the goods and services whose production processes are being automated, making households effectively richer, and increasing the demand for all goods and services.” (Acemoglu and Restrepo, 2018b, *NBER*, p. 6).

CONVENTIONAL WISDOM (2)

This is exactly the classical compensation mechanism "via decreasing prices".

- A third main self-correcting force is "***capital accumulation***" which

  "*..triggered by increased automation (which raises the demand for capital) will also raise the demand for labor*" (Acemoglu and Restrepo, 2018b, *NBER*, p. 1).

  This is the classical compensation mechanism "**via new investments**"

- A fourth main self-correcting force is the "***reinstatement effect***":

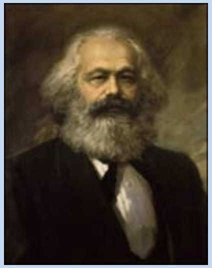
  "*We argue that there is a more powerful countervailing force that increases the demand for labor as well as the share of labor in national income: the creation of new tasks, functions and activities in which labor has a comparative advantage relative to machines*" (Acemoglu and Restrepo, 2018b, *NBER*, p. 2). (for instance in education, healthcare, augmented reality, see Acemoglu and Restrepo, 2019b, IZA, pp. 7-8).

  Although clumsy, this implicitly refers to the compensation mechanism "**via new products**" (see below).

CURRENT EMPIRICAL EVIDENCE

- Using the model described above, Acemoglu and Restrepo (2017→2020) analyze the effect of the increase of industrial robot usage (measured as IFR national penetration rates instrumented by Eurupean data!) between 1990 and 2007 in the US local labor markets. According to their 2SLS estimates, one more robot per thousand workers has a significant negative impact in terms of employment.
- Following exactly the same approach, Chiacchio et al. (2018) investigate the EU labor markets (116 NUTS regions in Finland, France, Germany, Italy, Spain, and Sweden). Their results suggest that robot introduction is negatively associated with the employment rate.
- Graetz and Michaels (2018) use more accurate but outdated panel data on robot adoption (IFR and EUKLEMS data to estimate the stock of robots per million hours worked) within industries in 17 countries from 1993 to 2007. In contrast with the previous studies, their estimates suggest that robots did not significantly reduce total employment, although they did reduce low-skilled workers' employment share.
- Dauth et al. (2017) propose a local empirical exercise on Germany using IFR data over the 1994-2014 time-span. They construct a measure of local robot exposure for every region. They find no evidence that robots cause total job losses, but they do affect the composition of aggregate employment (a negative impact on employment in the manufacturing sector counterbalanced by a positive spillover effect in the service sectors).

THE OTHER SIDE OF THE COIN: PRODUCT INNOVATION



As emphasized by Schumpeter (1912) in his seminal contribution, technological change cannot be reduced to the sole process innovation (potentially labour-saving). Indeed, the introduction of **new products** entails the raise of new branches of production and stimulate additional consumption. Enlarged production and higher consumption translate into higher demand and therefore higher employment.

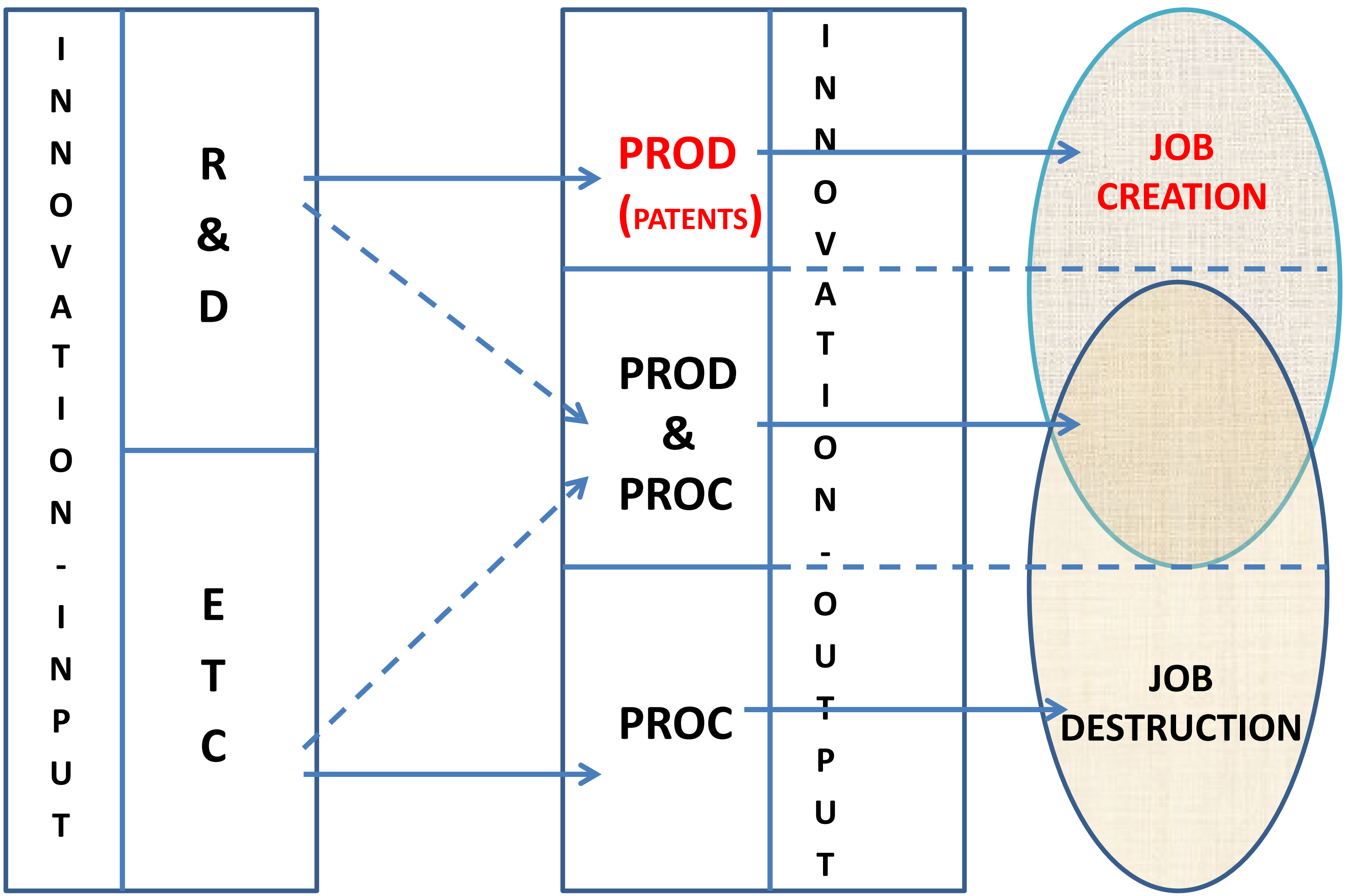
The **labour-friendly nature of product innovation** was even (and earlier) recognized by the most strict critic of the compensation theory:

" Entirely new branches of production, creating new fields of labour, are also formed, as the direct result either of machinery or of the general industrial changes brought about by it. But the places occupied by these branches in the general production is, even in the most developed countries, far from important" (Marx, 1961, vol. 1; p. 445 first ed. 1867).

HOWEVER, THE LABOUR-FRIENDLY NATURE OF PRODUCT INNOVATION SHOULD NOT BE OVER-EMPHASIZED

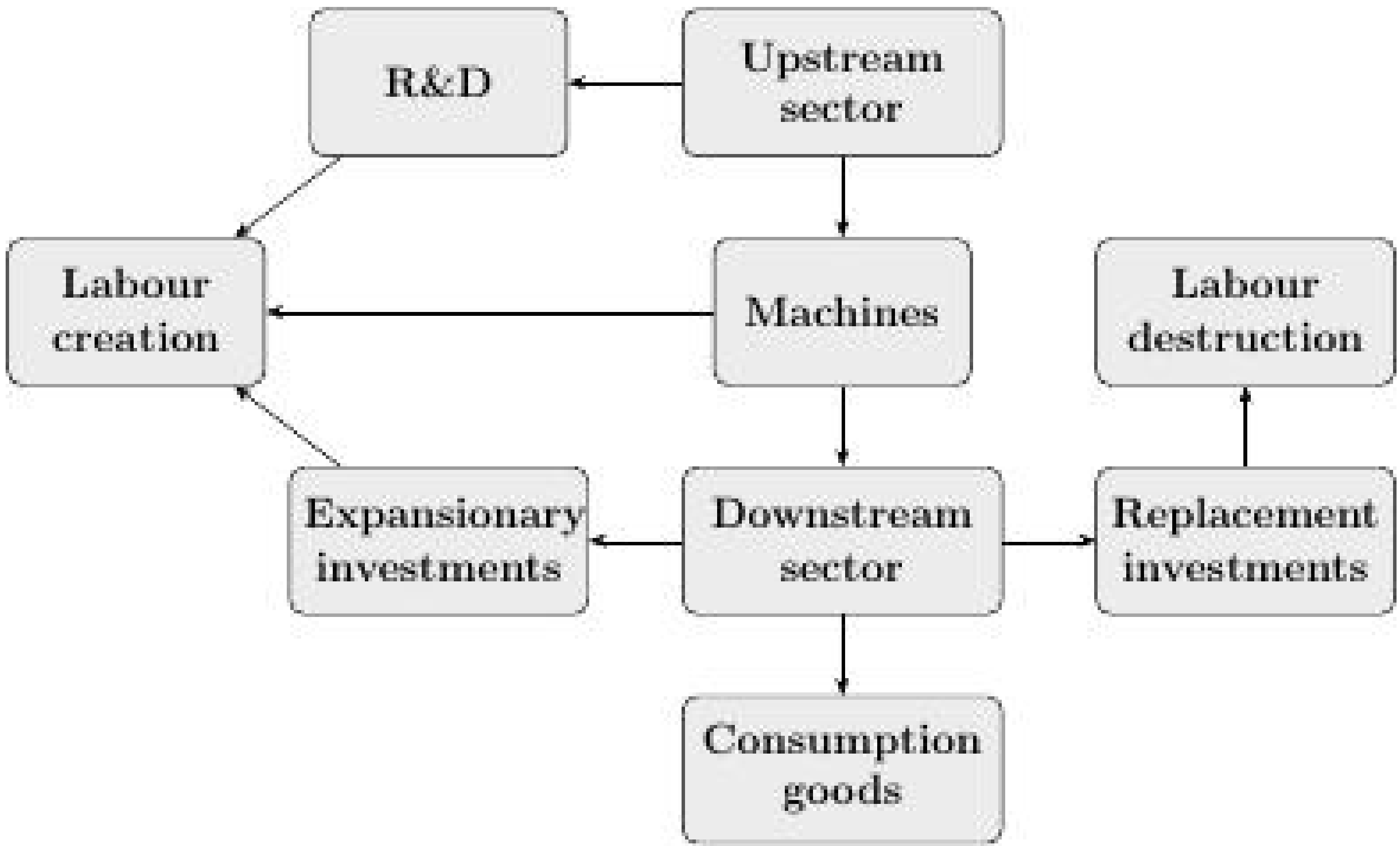
- First, the intensity of its impact depends on the **weight** that new products have in the baskets of consumption and on the **income elasticities** of their demand.
- Second, those which are new products for those producing them might well represent efficiency enhancing **processes for their users** (for instance: computers and robots)
- Third, in order to exert a compensating effect, new products should not exclusively replace obsolete ones. If new products just cannibalize the sales of old ones, the net result might be ambiguous. In other words, at the consumer level the "**welfare effect**" should be compared with the "**substitution effect**" (Katsoulacos, 1984 and 1986; Vivarelli, 1995)
- Fourth, product innovators may face a demand increase via market expansion, while the market shares of **non-innovators** may be eroded since old products become obsolete.
- Finally, new products may be produced more efficiently, due to the widespread evidence on the **complementarity** between product and process innovation.

A GUIDELINE TO EMPIRICAL TESTS (1)



A GUIDELINE TO EMPIRICAL TESTS (2)

(Dosi, G., Piva, M., Virgillito, M., Vivarelli, M. (2021), «Embodied and disembodied technological change: the sectoral patterns of job-creation and job-destruction", Research Policy, forthcoming, 2021)



THE ECONOMETRIC SPECIFICATION

$$l_{i,t} = \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 gi_{i,t} + \beta_4 LagInno_i + (\varepsilon_i + \nu_{i,t}) \qquad i = 1,..,n;\ t = 1,..,T$$

Taking into account **viscosity in the labor demand** (Arellano and Bond, 1991; Van Reenen, 1997), we move to the proper dynamic specification:

$$l_{i,t} = \alpha l_{i,t-1} + \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 gi_{i,t} + \beta_4 LagInno_i + (\varepsilon_i + \nu_{i,t})$$

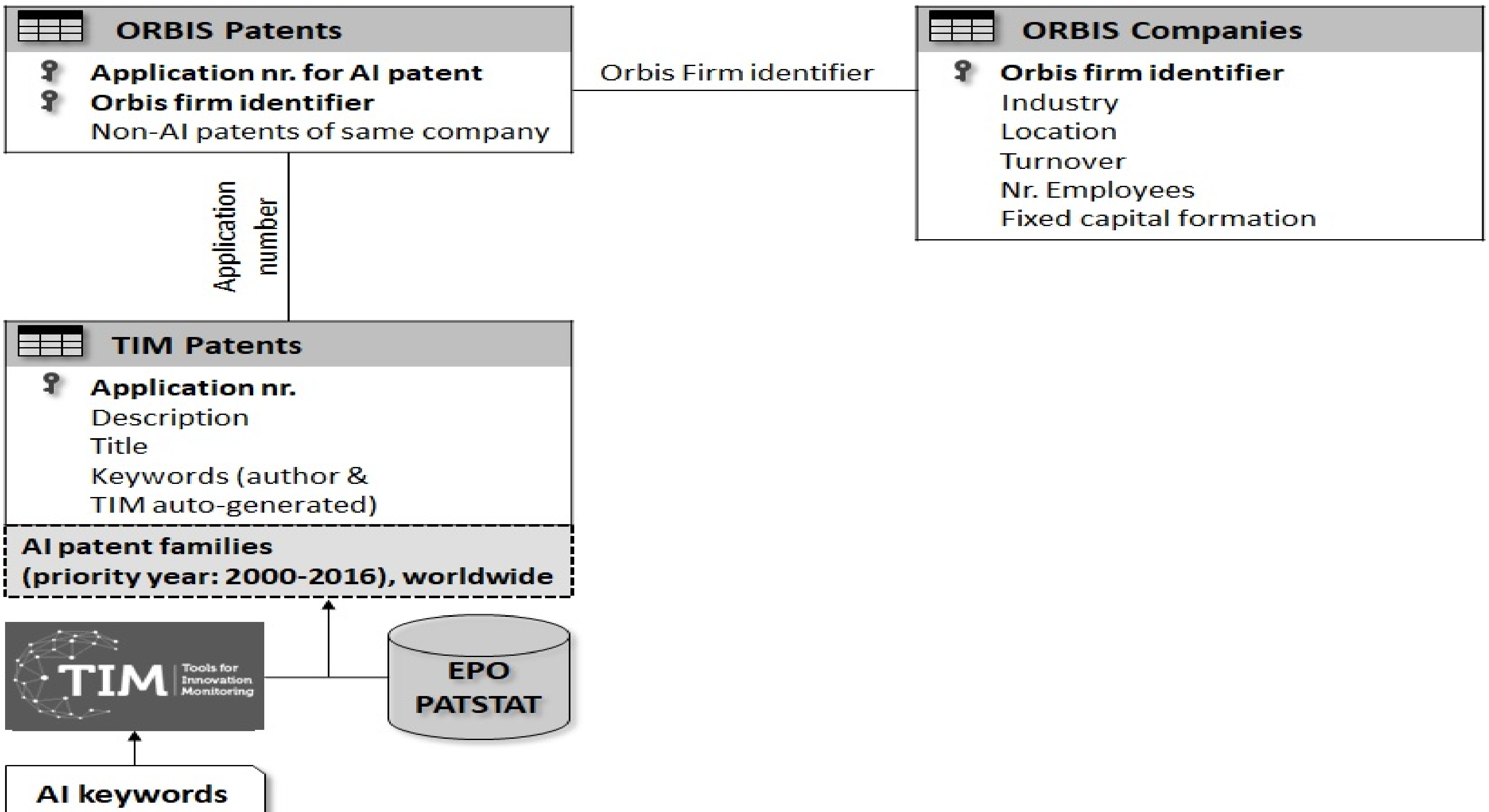
As common in the literature (see Van Reenen, 1997; Lachenmaier and Rottmann, 2011; Bogliacino, Piva and Vivarelli, 2012), this specification can be seen as a dynamic labor demand augmented by an innovation proxy.

Panel methodologies:

- **POLS** with time and sector dummies (endogeneity, unobservables not solved)
- **FE/RE** according to the Hausman's test, with time dummies (endogeneity not solved)
- **GMM-SYS** better than GMM-DIF because of strong persistence and dominant cross sectional variability; see Blundell and Bond, 1998 (preferred methodology, when feasible)
- Moreover, **endogeneity** may also affect other covariates in the model (for instance, it may well be the case that wage, investment and employment decisions are jointly and simultaneously adopted). Hence, all the explanatory variables will be cautiously considered as potentially endogenous to labour demand and instrumented when necessary, using up to thrice lagged instruments.
- Since all the variables are expressed in log, the estimated coefficients can be interpreted as **elasticities**.

DATA SOURCES

1. Identify AI patent families worldwide using a keyword-based (AI-aided) approach
2. Link patents to corporate balance sheet data (ORBIS) – see Van Roy et al (2020)
3. Collect patents in non-AI technologies for selected firms



CLEANING ORBIS DATA

Step 1: identify and treat clerical errors and typos for key financial variables (**employees**, **turnover**, **fixed assets** and **cost of employees** variables [i.e.: ‘000 errors]);
for **nr. employees**, impute values missing between two known time points not more than 4 years apart (typically unfilled values). Did not impute K or wage data due to high annual fluctuation.
(followed Hallak and Harasztosi, 2019)

Step 2: Remove outlier *year-on-year growth rates* in key financial vars (by size class, typically <1% of tails, following Van Roy et al, 2018). Thresholds:

	Micro	**Small**	**Medium**	**Large**
vars	**(>=10)**	**(10-50)**	**(50-250)**	**250<**
EMPL	3; -0.9	3; -0.9	2.6; -0.9	2; -0.9
TURN, K, COST EMPL	25; -0.96	10; -0.96	6; -0.96	4; -0.96

Step 3: Trim top 1 percentile in terms of *levels* for Empl, Turn, K, Empl.cost/empl., patent appl

DATA DESCRIPTIVES

Variable	Mean	SD	Min	Max
Log(Employees)	5.12	2.56	0.00	12.29
Log(Employees) t-1	5.07	2.58	0.00	12.58
Log(Turnover)	17.17	3.01	0.00	24.99
Log(Cost of labour per Employee)	10.01	1.08	1.20	12.95
Log(Gross investment)	0.09	0.54	-17.64	2.30
Log(AI patent applications)	0.14	0.39	0.00	4.37
Log(Non-AI patent applications)	1.47	1.70	0.00	7.24
Log(AI patent family size)	0.13	0.36	0.00	3.96
Log(non-AI patent family size)	0.68	0.66	0.00	3.82

RESULTS (WHOLE SAMPLE)

	PATENTS			PATENT FAMILY SIZE		
	OLS	FE	Sys. GMM	OLS	FE	Sys. GMM
Log(Employees) t-1	0.854***	0.495***	0.523***	0.857***	0.500***	0.532***
	(0.010)	(0.027)	(0.034)	(0.010)	(0.028)	(0.035)
Log(Turnover)	0.107***	0.208***	0.257***	0.109***	0.210***	0.264***
	(0.009)	(0.028)	(0.041)	(0.009)	(0.028)	(0.041)
Log(Cost of labour per Employee)	-0.094***	-0.231***	-0.518***	-0.094***	-0.231***	-0.528***
	(0.007)	(0.016)	(0.035)	(0.007)	(0.016)	(0.036)
Log(Gross investment)	0.100***	0.058***	0.033**	0.100***	0.059***	0.033**
	(0.012)	(0.009)	(0.015)	(0.012)	(0.009)	(0.015)
Log(AI patent applications)	0.002	0.020***	0.034***			
	(0.006)	(0.006)	(0.013)			
Log(Non-AI patent applications)	0.017***	0.035***	0.028***			
	(0.002)	(0.004)	(0.009)			
Log(AI patent family size)				0.022***	0.024***	0.028***
				(0.006)	(0.006)	(0.010)
Log(non-AI patent family size)				0.024***	0.030***	0.014
				(0.005)	(0.006)	(0.009)
Constant	0.611***	1.346***		0.559***	1.304***	
	(0.121)	(0.354)		(0.122)	(0.355)	
Wald time-dummies			92449***			555160***
Hansen test (p-value)			6.560e+08***			2.880e+13***
AR (3)			-0.585			-0.430
R2 (overall)	0.986	0.636		0.986	0.634	
Obs.	26,137	26,137	26,137	26,137	26,137	26,137
N. of firms	3510	3510	3,510	3,510	3,510	3,510

OVERALL RESULTS (ZOOM)

	PATENTS			PATENT FAMILY SIZE		
	OLS	FE	Sys. GMM	OLS	FE	Sys. GMM
Log(AI patent applications)	0.002	0.020***	0.034***			
	(0.006)	(0.006)	(0.013)			
Log(Non-AI patent applications)	0.017***	0.035***	0.028***			
	(0.002)	(0.004)	(0.009)			
Log(AI patent family size)				0.022***	0.024***	0.028***
				(0.006)	(0.006)	(0.010)
Log(non-AI patent family size)				0.024***	0.030***	0.014
				(0.005)	(0.006)	(0.009)

GMM-SYS RESULTS (SPLIT SAMPLES)

- **Industries**
  - Services
  - Manufacturing
- **Firm's age**
  - Founded before 90
  - Founded after 90
- **AI intensity**
  - AI specialised
  - Non-AI specialised

GMM-SYS RESULTS (SPLIT SAMPLES)

	INDUSTRIES			
	SERVICES		MANUF.	
Log(Employees) t-1	0.539***	0.552***	0.479***	0.487***
	(0.045)	(0.046)	(0.047)	(0.048)
Log(Turnover)	0.205***	0.211***	0.256***	0.264***
	(0.048)	(0.048)	(0.053)	(0.054)
Log(Cost of labour per Employee)	-0.433***	-0.448***	-0.569***	-0.574***
	(0.044)	(0.044)	(0.057)	(0.058)
Log(Gross investment)	0.024*	0.024*	0.053*	0.055*
	(0.013)	(0.013)	(0.030)	(0.031)
Log(AI patent applications)	0.047**		0.019	
	(0.021)		(0.015)	
Log(Non-AI patent applications)	0.052***		0.010	
	(0.015)		(0.011)	
Log(AI patent family size)		0.048***		0.014
		(0.015)		(0.012)
Log(non-AI patent family size)		0.035**		-0.002
		(0.014)		(0.011)
Wald time-dummies	3897***	3640***	337965***	13370***
Hansen test (p-value)	1106***	585.9***	33.36***	30.96***
AR (2) or AR (3)	-0.943	-1.030	-0.510	-0.323
Obs.	10,871	10,871	15,266	15,266
N. of firms	1,573	1,573	1,937	1,937

GMM-SYS RESULTS (SPLIT SAMPLES)

	FIRM'S AGE			
	FOUNDED BEFORE 1990		FOUNDED AFTER 1990	
Log(Employees) t-1	0.274***	0.285***	0.553***	0.567***
	(0.063)	(0.065)	(0.038)	(0.039)
Log(Turnover)	0.386***	0.383***	0.210***	0.225***
	(0.114)	(0.113)	(0.037)	(0.037)
Log(Cost of labour per Employee)	-0.650***	-0.664***	-0.465***	-0.472***
	(0.107)	(0.106)	(0.034)	(0.034)
Log(Gross investment)	0.086*	0.086*	0.028***	0.027***
	(0.051)	(0.051)	(0.010)	(0.010)
Log(AI patent applications)	0.014		0.044***	
	(0.022)		(0.015)	
Log(Non-AI patent applications)	0.007		0.035***	
	(0.019)		(0.010)	
Log(AI patent family size)		-0.003		0.042***
		(0.016)		(0.012)
Log(non-AI patent family size)		0.005		0.013
		(0.017)		(0.010)
Wald time-dummies	329.4***	349.4***	461221***	374500***
Hansen test (p-value)	4.320e+10***	1.840e+10***	51.35***	2.050e+24***
AR (2)	-1.444	-1.615	-0.705	-0.803
Obs.	9,933	9,933	16,204	16,204
N. of firms	1,165	1,165	2,345	2,345

GMM-SYS RESULTS (SPLIT SAMPLES)

	AI INTENSITY			
	AI SPECIALISED		NON-AI-SPECIALISED	
Log(Employees) t-1	0.579***	0.583***	0.458***	0.464***
	(0.037)	(0.036)	(0.050)	(0.052)
Log(Turnover)	0.207***	0.210***	0.290***	0.308***
	(0.043)	(0.043)	(0.075)	(0.076)
Log(Cost of labour per Employee)	-0.495***	-0.498***	-0.511***	-0.520***
	(0.039)	(0.039)	(0.048)	(0.048)
Log(Gross investment)	0.022*	0.021	0.053**	0.055**
	(0.013)	(0.013)	(0.026)	(0.027)
Log(AI patent applications)	0.046***		0.017	
	(0.016)		(0.016)	
Log(Non-AI patent applications)	0.040***		0.016	
	(0.010)		(0.010)	
Log(AI patent family size)		0.039***		0.009
		(0.015)		(0.011)
Log(non-AI patent family size)		0.031***		0.005
		(0.010)		(0.010)
Wald time-dummies	49771***	63761***	3.005e+06***	1.271e+06***
Hansen test (p-value)	48.91***	1.680e+10***	30.61***	7.480e+09***
AR (2) or AR (3)	-0.981	-1.003	-1.206	-1.337
Obs.	12,994	12,994	16,786	16,786
N. of firms	1,839	1,839	2,102	2,102

GMM-SYS SPLIT RESULTS (ZOOM)

	INDUSTRIES			
	SERVICES		MANUF.	
Log(AI patent applications)	0.047**		0.019	
	(0.021)		(0.015)	
Log(Non-AI patent applications)	0.052***		0.010	
	(0.015)		(0.011)	
Log(AI patent family size)		0.048***		0.014
		(0.015)		(0.012)
Log(non-AI patent family size)		0.035**		-0.002
		(0.014)		(0.011)
	FIRM'S AGE			
	FOUNDED BEFORE 1990		FOUNDED AFTER 1990	
Log(AI patent applications)	0.014		0.044***	
	(0.022)		(0.015)	
Log(Non-AI patent applications)	0.007		0.035***	
	(0.019)		(0.010)	
Log(AI patent family size)		-0.003		0.042***
		(0.016)		(0.012)
Log(non-AI patent family size)		0.005		0.013
		(0.017)		(0.010)
	AI INTENSITY			
	AI SPECIALISED		NON-AI-SPECIALISED	
Log(AI patent applications)	0.046***		0.017	
	(0.016)		(0.016)	
Log(Non-AI patent applications)	0.040***		0.016	
	(0.010)		(0.010)	
Log(AI patent family size)		0.039***		0.009
		(0.015)		(0.011)
Log(non-AI patent family size)		0.031***		0.005
		(0.010)		(0.010)

KEY FINDINGS

- Our findings indeed reveal a **positive and significant impact of AI patent applications on employment**, supporting the labour-friendly nature of product innovation in the supply industries.
- However, this job-creation effect is **small in magnitude** (3/4%) and unlikely able to compensate the labour-saving effect in the downstream industries.
- The positive employment impact is limited to **service sectors and younger firms**, that is in the leading actors of AI revolution.
- Some evidence of **increasing returns** seem to emerge: indeed, the innovative companies which are more focused on AI technologies are those obtaining the larger effects in terms of job creation.
- These pieces of evidence suggest that the technological leaders within the emergence of the AI paradigm can realize (modest) labour-friendly outcomes; however, **heterogeneity** is also detected, with manufacturing, older and less innovative companies unable to couple product innovation with job creation.

THANK YOU

KEY WORDS on AI

Keywords related to artificial intelligence		
Artificial intelligence	Face recognition	Random Forest
Artificial intelligent	Facial recognition	Reinforcement learning
Artificial reality	Gesture recognition	Robotics
Augmented realities	Holographic display	Self driv
Augmented reality	Humanoid robot	Sentiment analysis
Automatic classification	Internet of things	Smart glasses
Autonomous car	Knowledge Representation	Speech Recognition
Autonomous vehicle	Machine intelligence	Statistical Learning
Bayesian modelling	Machine learn	Supervised learning
Big data	Machine to machine	Transfer Learning
Computational neuroscience	Mixed reality	Unmanned Aerial Vehicle
Computer Vision	Natural Language Processing	Unmanned aircraft system
Data mining	Neural Network	Unsupervised learning
Data science	Neuro-Linguistic Programming	Virtual reality
Decision tree	Object detection	Voice recognition
Deep learn	Predictive modeling	
Evolutionary Computation	Probabilistic modeling	